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Hyperspectral aerial imagery for detecting nitrogen stress in two potato cultivars

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ABSTRACT

To use remotely sensed spectral data for determining rates and timing of variable rate nitrogen (N) applications at a commercial scale, the most reliable indicators of crop N status must be determined. This study evaluated the ability of hyperspectral remote sensing to predict N stress in potatoes (*Solanum tuberosum*) during two growing seasons (2010 and 2011). Spectral data were evaluated using ground based measurements of leaf N concentration. Two canopy-scale hyperspectral images were acquired with an AISA-Eagle hyperspectral camera in both years. The experiment included five N treatments with varying rates and timing of N fertilizer and two potato cultivars, Russet Burbank (RB) and Alpine Russet (AR). Partial Least Squares regression (PLS) models resulted in the best prediction of leaf N concentration ($r^2 = 0.79$, Root Mean Square Error of Cross Validation (RMSECV) = 14% across dates for RB; $r^2 = 0.77$, RMSECV = 13% across dates for AR). Applying the Nitrogen Sufficiency Index (NSI) formula to spectral indices/models made them mostly insensitive to the effects of cultivar. The most promising technique for determining N stress in potato based on spectral indices was found to be the MERIS Terrestrial Chlorophyll Index (MTCI) due to a combination of relatively high r^2 values, lower RMSECVs, and high accuracy assessment. Pairwise comparison tests from the means separation showed that spectral indices/models from the imagery resulted in more statistically significant groupings of crop stress levels for the spectra than leaf N concentration because canopy-scale spectral data are affected by both tissue N concentration and biomass. The results of this study suggest that upon proper sensor calibration, canopy-scale spectral data may be the most sensitive tool available to detect N status of a potato crop.

1. Introduction

Potato (*Solanum tuberosum* L.) is an important crop worldwide, ranking first in 2010 among all other non-cereal food crops with over 324 million Mg produced (FAOSTAT, 2010). The coarse-textured soils typically used for irrigated potato production are relatively low in organic matter and cation exchange capacity, and therefore, are generally low in soil nutrient reserves. Potato plants are relatively shallow rooted compared to other field crops and are sensitive to nitrogen (N) and water stress (Bailey, 2000; Lesczynski and Tanner, 1976). Previous studies have shown that only about one-third to one-half of applied N is recovered in years of moderate to heavy leaching (Errebhi et al., 1998; Waddell et al., 2000). Therefore, precise N management is important for irrigated potatoes to optimize production and to minimize environmental N losses.

Abbreviations: MTCI, MERIS Terrestrial Chlorophyll Index; NUE, Nitrogen Use Efficiency; NO_3-N, Nitrate-Nitrogen; NH_4-N, Ammonium-Nitrogen; LAI, Leaf Area Index; NSI, Nitrogen Sufficiency Index; S, Surfactant; AISA, Airborne Imaging Spectrometer for Applications; CALMIT, Center for Advanced land Management Information Technologies; DAE, Days After Emergence; NIR, Near Infrared; PLS, Partial Least Squares Regression; LV, Latent Variables; PRESS, Predicted Residual Sum of Squares; ROI, Region of Interest; ANOVA, Analysis of Variance; RMSECV, Root Mean Square Error of Cross Validation; NG, Normalized Green; CV, Coefficient of Variation; RF, Relative Fluctuation; NDVI, Normalized Difference Vegetation Index; DCNI, Double-peak Canopy Nitrogen Index; NDI2, Normalized Difference Index 2; NNI, Nitrogen Nutrition Index; SR8, Simple Ratio 8.

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Matching the timing and rate of N fertilizer with the N needs of the crop during different growth stages is a strategy used to increase N Use Efficiency (NUE) and minimize N losses (Canter, 1997; Errebhi et al., 1998). The use of fertigation (i.e., the application of a water-soluble fertilizer through an irrigation system) provides a convenient method to split post-emergence N applications. The challenge lies in the ability to estimate the appropriate rate and timing of split N applications so that fertilizer N best matches crop demands. This is because crop uptake rates and soil N transformations/losses depend on the interaction of many complicated and sometimes unpredictable factors throughout the growing season, including: fertilizer source, soil fertility, physical soil properties, and weather conditions (Gupta et al., 1997; Mamo et al., 2003).

A current best management practice for potato production on coarse-textured soils is to base the rate and timing of post-emergence N fertilizer applications on petiole Nitrate-Nitrogen (NO_3-N) concentrations (Zebarth and Rosen, 2007). The limitation of petiole analysis is that it uses point sampling, and it does not account for within-field spatial variability at a fine spatial scale. Remote sensing of the crop canopy is better suited for precision agriculture applications because of its ability to cover large areas at fine spatial resolutions, usually in a fraction of the time. This provides a major advantage over using point measurements such as petiole samples for N stress determination.

A major limitation to the widespread use of remote sensing for making N fertilizer recommendations is the difficulty in identifying spectral algorithms and calibration procedures that are reliable over many growing conditions such as soil types, growth stages, cultivars, and weather (Samborski et al., 2009). In an operational setting, remote sensing alone cannot differentiate whether N status at a particular time and place is related to soil, growth stage, cultivar, weather, or management. Therefore, it is essential that differences among these factors are understood, so objective protocols can be developed for accurate and reliable variable rate N fertilization over many growing conditions.

Remote sensing has been effectively used in many crops to predict biophysical parameters that depend on crop N uptake, such as Leaf Area Index (LAI), tissue N or NO_3-N concentration, and leaf chlorophyll content (Reyniers et al., 2006; Lamb et al., 2002; Chen et al., 2010; Cohen et al., 2010; Haboudane et al., 2004, 2008). Spectral data acquired during the growing season can be used to monitor crop N status because spectral characteristics of green vegetation change as leaf chlorophyll content changes, and N is closely related to chlorophyll in plant cell metabolism (Stroppiana et al., 2012). Hundreds of spectral indices have been developed with the aim of predicting particular plant biophysical parameters while minimizing the effects of solar irradiance and soil background (Jackson and Huete, 1991; Rees, 2001).

Hyperspectral imagery is a powerful research tool that can be used to monitor crop N status at a high spatial scale over a variety of conditions and growth stages, therefore making it suitable for precision agriculture applications (Mulla, 2012). Chemometric models that use all hyperspectral wavebands (e.g., partial least squares regression or principal components analysis) have been found to predict crop biophysical parameters well, especially for leaf N concentration (Cohen et al., 2010; Hansen and Schjoerring, 2003; Nguyen et al., 2006).

Research on aerial-based hyperspectral imagery for N sufficiency in potatoes, specifically using chemometric models to make variable rate management decisions under various cultural conditions, has not been previously published. The main purpose of this study was to determine the approaches necessary to make spectral data more versatile across environments (i.e., cultivars and growth stages) so it can be easily calibrated and used for detecting N stress in a potato crop. Three objectives were defined to complete this task: (i) determine the relationship between spectral data and leaf N concentration and determine the ability of these measurements to detect differences among N treatments, (ii) evaluate the differences in variability across experimental treatments for various spectral indices/models, and (iii) evaluate the ability of spectral indices/models to classify N Sufficiency Index (NSI) stress levels into pre-determined N stress classes using an accuracy assessment procedure.

2. Materials and methods

2.1. Study site

Field experiments were conducted over 2 years (2010–2011) at the University of Minnesota Sand Plain Research Farm (45°23′N, 95°53′W) near Becker, MN. The soil at this location is classified as an excessively drained Hubbard loamy sand (sandy, mixed, frigid Typic Hapludoll) comprised of 82% sand, 10% silt, and 8% clay. The available water holding capacity in the upper 120 cm of soil is 85.1 mm. Irrigation was applied to the treatment plots with an overhead sprinkler system; rates and timing of application were scheduled using a water balance method (Wright, 2002). In 2010 and 2011, 32 cm and 26 cm of irrigation were applied, respectively. Timing of irrigation was variable between years and depended on weather conditions. Rainfall and irrigation data throughout each growing season are presented in Nigon (2012). After rainfall (80 cm in 2010 and 64 cm in 2011), total cumulative water at the end of the growing season was 112 and 90 cm in 2010 and 2011, respectively. During the growing season (April–September), the 30-year average (1971–2000) temperature and rainfall are 16.5 °C and 550 mm, respectively (Midwest Regional Climate Center). Soil drainage was calculated as part of the general water budget equation (Errebhi et al., 1998), in which the Penman–Monteith equation was used to calculate daily evapotranspiration (as described by Venterea et al., 2011). Cumulative soil drainage from planting through the second image date was 401 mm in 2010 and 402 mm in 2011. During this time frame, there were 40 and 21 drainage events greater than 5.0 mm in 2010 and 2011, respectively. The previous crop in both years was non-irrigated cereal rye (*Secale cereal* L.). Pre-plant KCl extractable soil N (NH_4-N + NO_3-N) in the upper 60 cm was 15 kg ha^{-1} in 2010 and 20 kg ha^{-1} in 2011 (Nigon, 2012).

2.2. Experimental design

This experiment was set up using a randomized complete block design with a split plot restriction on randomization replicated four times. The whole plot treatment included a low, medium, and high N rate (i.e., 34, 180, and 270 kg N ha^{-1}) with variable timing of post-emergence N applications for the high rate, for a total of five N treatments (i.e., 34 early, 180 split, 270 split, 270 split + surfactant (s), and 270 early; Table 1). Treatments 270 split and 270 split + s had the same rate and timing of N application, but a soil surfactant (IrrigAid Gold) was applied to 270 split + s at a rate of 10 L ha^{-1} to investigate the effects of the surfactant on improving NUE. Because treatments 180 split, 270 split, and 270 split + s had split applications of post-emergence N fertilizer, actual N applied at the time of remote sensing data acquisition varied (Table 2). All N applications were completed by the later image date in 2010, but one post-emergence N application remained at the later image date in 2011. In each year, the planting and emergence N source was mono-ammonium phosphate and urea, respectively. The subplot treatment consisted of two potato cultivars: Russet Burbank (RB) and Alpine Russet (AR; Whitworth et al., 2011).